

Biomechanical Changes to Human Locomotion  
Due to Asymmetric Loading of the Legs

by

Wesley D. McDougal

Submitted to the  
Department of Mechanical Engineering  
in Partial Fulfillment of the Requirements for the Degree of

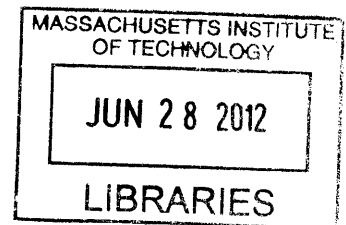
Bachelor of Science in Mechanical Engineering

at the

Massachusetts Institute of Technology

June 2012

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## ABSTRACT

The biomechanics of lower limb locomotion is a yet unknown mixture of neurological control and physical parameters. The current study explored attaching a rehabilitative anklebot to subjects walking on a treadmill and observed duration, kinematic, and electromyography data to determine the biomechanical response to the asymmetric loading.

The present report identified various gait cycle parameters that changed as a response to the asymmetric loading. Notably, significant differences in the stride time of the legs occurred under loading, while contralateral stride times also adjusted to remain equal to those of the loaded legs.

Symmetry index analysis led to the conclusion that, while the asymmetric loading of the lower limbs had some effects on temporal gait parameters, the body adjusted to minimize any temporal asymmetry. However, goniometer data demonstrated kinematic changes in response to loading as knee flexion peaked earlier in the gait cycle.

Thesis Supervisor: Neville Hogan

Title: Sun Jae Professor of Mechanical Engineering



## **Acknowledgements**

This work, and MIT in general has been a massive learning process, and I want to give thanks to everyone who has helped me throughout the experience.

First I want to thank Prof. Hogan for his oversight, guidance, and thoughtful, patient critique of the thesis process. I really learned this semester, and thank you for helping me in that process.

Also Hyunglae – thanks for spending so much time making sure I knew what I was doing and was doing it right. The ideas and guidance you provided were invaluable. Shuo, thanks for showing me the ropes around the lab.

Thanks to my friends, who helped me when I got stuck on analysis, looked at MATLAB code with me, and fake limped all around the house and campus so I could think about asymmetry. Thank you all for providing the daily encouragement and support that the project needed.

Finally, thanks to my amazing family and their eternal support, especially to my parents, who started the learning journey with me and now get to finish the official schooling process with me. The eternal reminders and support have been a bigger blessing than I can describe.

Dei Gratia - one step at a time.



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## **1.Introduction**

The effects of asymmetric loading of the lower limbs is of great importance to both biomedical researchers hoping to restore normal human gait and to biomechanics researchers searching to better understand the neurological control of walking that the nervous system exerts in human locomotion. Although many studies have investigated the effects of weight-loading the lower limbs, the complete kinematics and neurological control of the locomotion system are not fully understood.

In the biomedical field, the effects of asymmetric loading of the lower limbs are of particular importance for lower limb prosthesis and orthosis users. In particular, the need to understand the effects of and training for lower limb ambulatory devices is crucial for the well-being of the users, both to minimize health risks and improve the overall quality of life for the subject (1). One primary influence on the gait cycle is the loading of the lower limbs; this factor is the subject of a great deal of study for lower limb prosthetics (2).

For researchers investigating the neural control of movement, the reaction of the lower limbs to loading could provide deeper insight to a field where, although much research has been done, there is still a great deal of uncertainty about the workings and organization of the neural control system (3)(4). While looking at the control of lower limb locomotion under loading may not yield a complete description of the neural control system, the loading's effect on lower limbs may answer critical questions about the control and regulation of walking.

Finally, the results of asymmetric loading are of particular importance to stroke patients using lower limb rehabilitation robots to aid with impaired locomotion. Stroke patients form a substantial portion of the United States population, with approximately 795,00 stroke victims each year (5). Although then number of deaths from strokes has been dropping over the last few years, the number of incidents with residual motor deficits is still staggering, with 50% of stroke survivors over the age of 65 struggling with hemiparesis (5).

This proliferation of stroke survivors with motor-deficit has led to the development of medical robots to assist with locomotion retraining. There are several available robotic assisted gait therapy

devices, from exoskeletons such as the Lokomat, AutoAmbulator, and LOPES, to moveable footplates such as Gait Trainer I and the Haptic Walker (6). With such devices, a primary concern is the propensity to preclude or at least disrupt preclude normal walking (7). Several studies have shown that robotic loading of hemiparetic patients leads to changes in kinematics (7), but the complete nature of disturbed motion introduced by the loading is yet to be fully characterized.

A recent study by Khanna et al. (2010) sought to ascertain the effects of asymmetrically loading hemiparetic subjects with an unpowered ankle robot. While they found slight variations in the kinematics of the leg, specifically reduction in nonparetic peak knee flexion during treadmill walking, there were no observable changes in the symmetry of the stroke survivor (7). However, this is not the output one would expect, because if the physical parameters of the system changed, one would also expect corresponding biomechanical changes. Thus, under the influence of a physical change such as loading, it follows that either the duration, kinematic, or muscle output parameters would adjust to retain walking performance.

As such, several questions remain from the Khanna et al. study. In particular, their investigation looked at subjects with significant hemiparesis; this impairment affected their walking speed, shortened the number of strides available for measurement, necessitated handrail used to help support body weight, and predisposed subjects display significant asymmetry between the paretic and nonparetic legs before loading (7).

For this paper, the author investigated the biomechanical effects of asymmetrically loading a single lower limb. The study strove to further investigate the results reported by Khanna et al. by examining healthy, young subjects, thereby isolating the effects of the robotic loading of the leg. In addition, this study incorporated observations of the EMG activity of the legs, while retaining observations of the kinematics and temporal aspects of the gait cycle.

## 2. Details/Experimental Setup

### 2.1 Overview

Healthy subjects were asked to walk on a treadmill for 2 ten minute intervals. They alternated between unloaded, normal walking, and asymmetric loading of a single limb using an unpowered robot. Foot switches, goniometers, and electromyography (EMG) sensors were used to record data.

### 2.2 Apparatus

The effects of loading were achieved by attaching an unpowered ankle robot to the knee of the subjects. This study used MIT's Anklebot, the same anklebot used by Khanna et al. Developed for the dual purpose of assisting in the rehabilitation of stroke survivors and characterizing ankle properties, the anklebot exhibits low mechanical impedance with minimal friction and backdrivability. Weighing approximately 3.6 Kg, the robot possesses 3 degrees of freedom, which allowed subjects to demonstrate the full range of motion required for locomotion (8). The anklebot was attached to the leg through a specialty knee-brace and specialty shoes with u-brackets for support.<sup>a</sup>

The variables of walking observed were the kinematics, heel strike moment, and EMG activity of selected leg muscles. The kinematics were recorded through single axis, fiber optic goniometers from Delsys® biosignal sensors. The sensors were calibrated by positioning the goniometers at known angles and recording the output voltage.<sup>b</sup> Unfortunately, the performance of these goniometers left much to be desired, as repeated trials revealed an output with extremely low precision.

Foot switches from Delsys®' biosignal sensor selection were employed to determine the moment of heel strike. The Delsys Surface EMG sensors were also used to record muscle activation data. All data were captured through a DelsysMyomonitor® IV Wireless Transmission & Datalogging System.

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<sup>a</sup>See Figure 2(b)

<sup>b</sup>For more details on the goniometers' calibration, see Appendix A

## 2.3 Subjects

The subjects for this study were young, healthy adults, 2 male and 1 female. However, it must be noted that Subject 1 reported a traumatic injury to the dominant knee two years previously. He also self-reported a return to normal gait since the injury. Therefore, the anklebot was tested upon Subject 1's non-dominant leg (henceforth called the "dominant leg" for consistency across all subjects).

Other biographical and physical information can be found in Table 1. All subjects volunteered to participate in the study and signed consent forms as approved by MIT's Committee on the Use of Humans as Experimental Subjects.

**TABLE 1:** Subject Biographical and Physiological Data

Subject Data						
Subject	Sex	Age (Years)	Leg Dominance	Height (cm)	Weight (kg)	Healthy?
#1	M	21	L (Change to R)	187	72	Y but Post Trauma
#2	F	22	R	163	66	Y
#3	M	32	R	172	61	Y

## 2.4 Experimental Methods

The experiment was setup and run by the author and lab research supervisors, who helped attach the sensors to the subject. The foot switches were first placed beneath the calcaneus, on the center of the subjects' heels (beneath their socks).

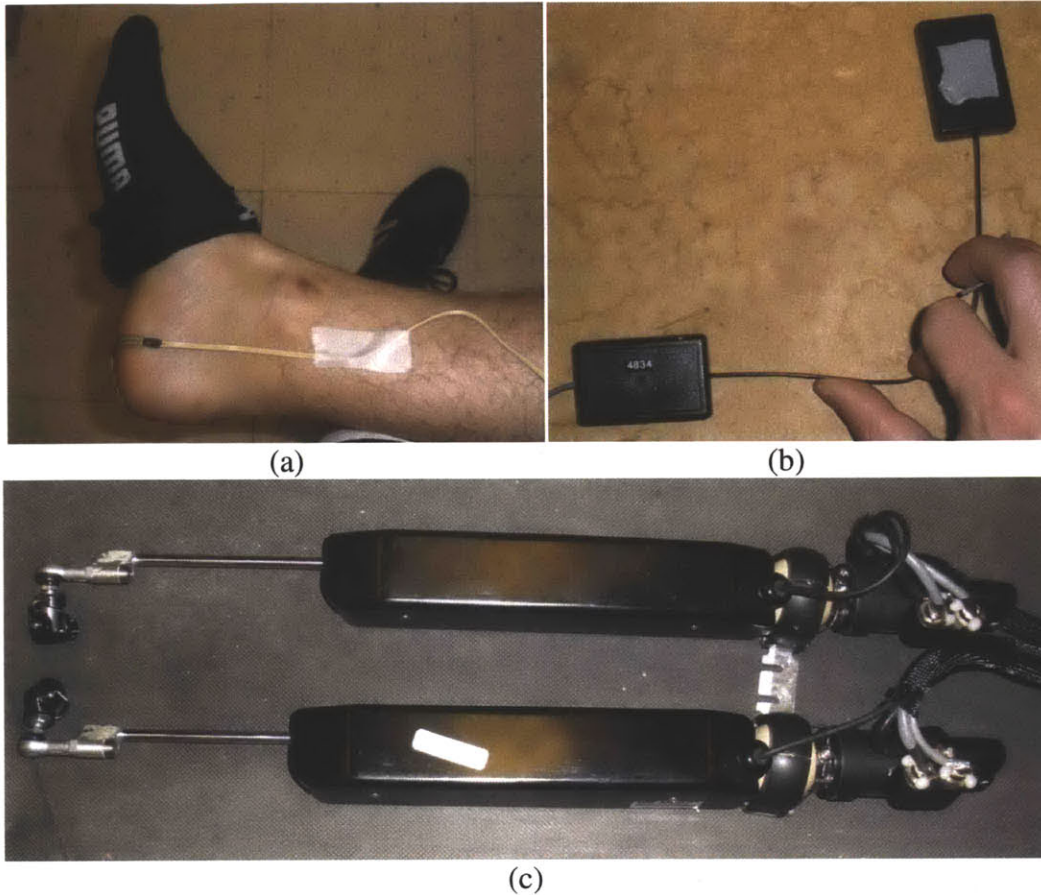
The knee and ankle goniometers were then carefully attached. Subjects 1 and 2 used standard medical tape as attachment mechanisms, while Subject 3 had the back of the goniometers outfitted with double sided Scotch® Mounting Tape. We strongly recommend further use of the mounting tape, as it created a much more stable attachment method as well as improved patient comfort (by significantly reducing the amount of medical tape required).

When attaching the goniometer to the knee, care was taken to ensure that the goniometer was still flexed when the knee reached full extension in order to avoid passing through the fully extended configuration of the goniometer. The goniometer was attached to the ventral side of the knee to measure sagittal plane motion, with care being taken in the placement to ensure that the knee brace for the anklebot could fit over the goniometer without disrupting the position of the sensor. In addition, care was taken to place the center of the goniometer over the middle of the knee (lower edge of the patella) to try and obtain the best and most consistent output readings.<sup>c</sup>

The ankle goniometer was attached with tape as well, once again trying to ensure that the center of the goniometer passed through the center of rotation of the ankle. However, in the loaded condition, the strap on the anklebot shoe was also tightened around the goniometer to ensure position reinforcement.

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<sup>c</sup> See Figure 1 below for apparatus components and Figure 2 for sensor placement.



**Figure 1:** (a) The attachment of the foot switch below the sock. (b) The goniometer being held at a right angle along its rotation axis. Double sided mounting tape is seen on the upper-right hand block. (c) The unmounted anklebot apparatus lain horizontally on the ground. The wired end (right end in figure) was attached to the knee brace using the bracket spanning the gap, while the lower extensions (left side) attach to the anklebot shoe.



### 3. Data Analysis

Each 10 minute test produced over 470 strides (the shortened test for Subject 2's loaded condition produced 293 strides). The files were sent to EMGworks® Acquisition program, and converted to text files to be processed in using Matlab® (MathWorks®, Inc.).

#### 3.1 Duration

The foot switch and ankle goniometer for each leg were analyzed to provide duration data for gait cycle parameters. Moment of heel strike and stride duration (time between successive heel strikes of a given leg) were determined from the foot switch. Due to the limited number of sensor collection ports, no foot switch was used on the toe. However, toe-off was estimated using the ankle trajectory; the maximum ankle plantarflexion measurement was assumed to correspond to toe-off (9).

With the heel strike and estimated toe-off data, the duration of the stance phase (the period of gait from heel strike to toe-off) and its percent of whole gait cycle were calculated for both legs in both the loaded and unloaded conditions. In addition, a symmetry index was used to compare the dominant and non-dominant legs' percent stance phase. Employing the definition of symmetry used by Khanna et al. (2010), the symmetry index compares the percent stance phase symmetry between the left and right legs:

$$SI = \frac{1}{2} * \left| \frac{V_{dominant} - V_{non-dominant}}{V_{dominant} + V_{non-dominant}} \right| \quad (1)$$

where SI varies between 0 and 1, and V is the percent stance phase for a given leg. A lower value of SI indicates a greater symmetry (a zero value for SI indicates perfect symmetry).

In addition, the time between contralateral heel strikes was calculated from the foot switch data in order to determine the relative timing of the steps. This timing was defined as the time elapsed between dominant (or loaded) leg heel strike and non-dominant heel strike. In addition, this timing between heel strikes was evaluated as a percent of the entire gait cycle duration in order to observe any phase shift in the loading condition.



(a)



(b)

**Figure 2:** (a) Sensor setup of the dominant leg, including the goniometers, emg sensors, and foot switch. (b) Entire loaded configuration setup, with sensors and anklebot apparatus attached.

The EMG sensors were then applied to the quadriceps (rectus femoris), hamstrings (biceps femoris long head), tibialis anterior, and gastrocnemius muscles on both legs. Finally, a ground reference pad was attached to the knee cap. With the entire measurement system attached and in place, the subject was asked to walk on the treadmill and to pick a comfortable walking speed. Once the subject reached a speed they felt comfortable with, data collection started and continued for 10 minutes.<sup>d</sup>

The subject was then stopped and asked to place the anklebot knee-brace and robot over the sensors on the dominant leg. If the subject felt that the anklebot was unsecure on their leg, he was given a form of shoulder strap or harness support to help keep the anklebot in place and support the weight of the anklebot. The subject was then asked to walk on treadmill, quickly building up to the velocity previously used, and the ten minute trial was run again.

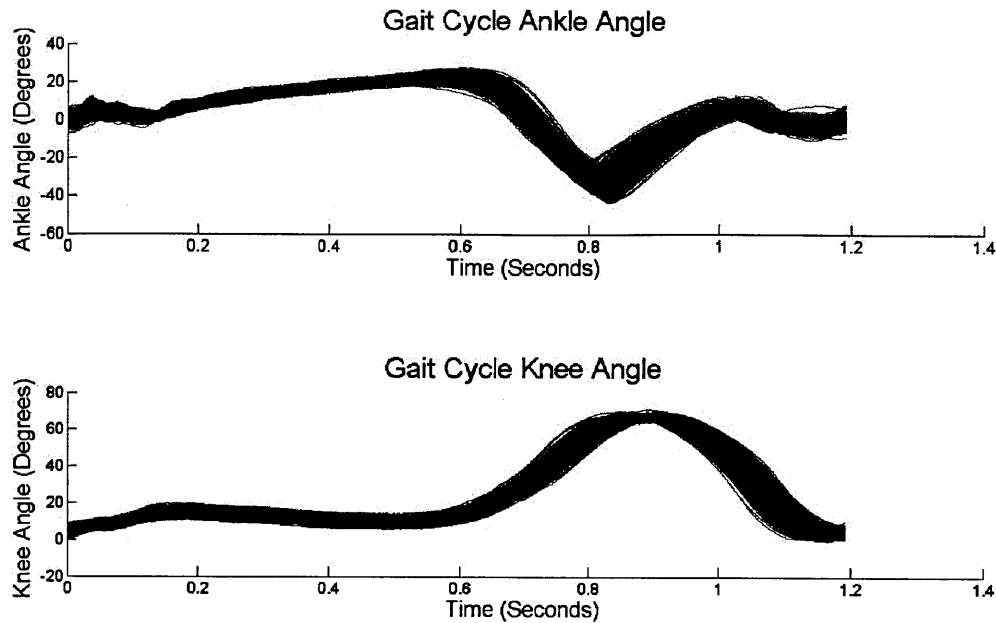
<sup>d</sup> Subject 2's loaded portion had to be cut short to 5 minutes due to scheduling.

## 3.2 Kinematics

The knee and ankle goniometer data from both legs were separated into individual gaits, normalized to the mean stride time, and overlaid to observe timing and amplitude patterns. The bias was removed from the results of both the ankle and knee data. The knee data was adjusted to reset the fully extended knee (straight – no hyperextension assumed) to zero degrees, with increasing flexion corresponding to an increasing angle. Meanwhile, the bias in the ankle data was removed by adjusting initial heel strike to zero degrees, with positive angles corresponding to dorsiflexion and negative angles corresponding to plantarflexion.

However, several of the goniometer output results yielded data that appeared to fall well beyond the biomechanical limits of feasible motion in walking. Thus, further analysis of the magnitude of peak angles in the knee and ankle's gait cycle was deferred to future investigation. In addition, the knee goniometers occasionally displayed saturation, making it impossible to clearly identify the peaks.

However, despite the issues with the scaling of the goniometers, they retained significant precision and accuracy in their temporal reliability, and as such the timing of peak angle occurrence could be compared in the loaded and unloaded conditions for both the ankle and knee. The un-normalized data was overlaid and the timing of the peak knee flexion and ankle plantarflexion were determined and expressed as a percent of the total gait cycle. This timing of peak ankle plantarflexion was used as the estimated toe-off point.



**Figure 3:** The prototypical gait cycle angles for a subject's ankle (top) and knee (bottom). Each of the strides was separated and overlaid, starting at the moment of heel strike. Positive ankle angles correspond to dorsiflexion, and positive knee angles correspond to flexion.

### 3.3 Muscle Activity

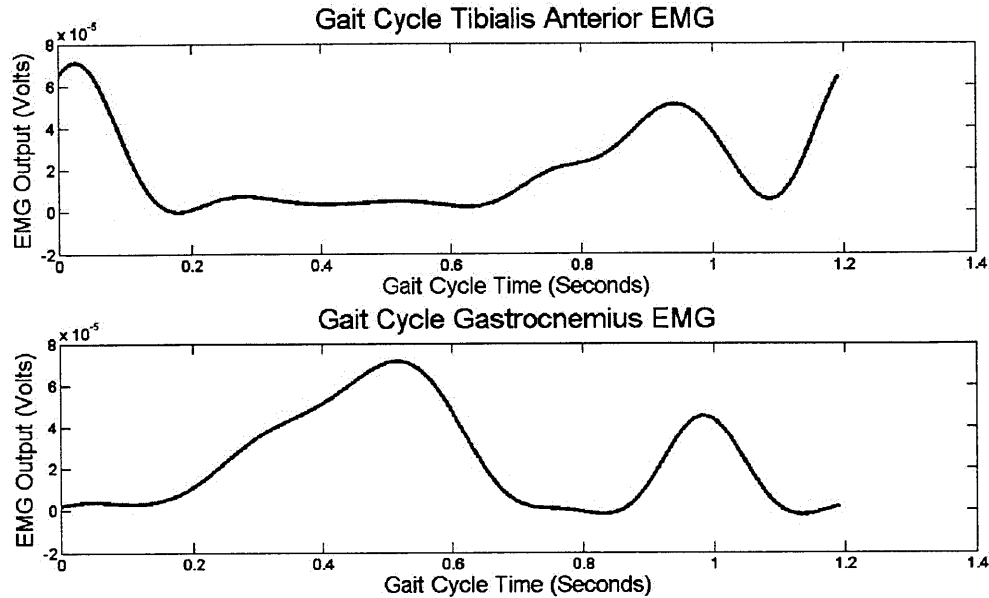
The EMG records were inspected for signals with excessive noise, saturation, and muscle activation frequency far below that of the usual range of EMG activity. Due to the pilot nature of the experiments, several EMG sensors repeatedly produced bad data that had to be excluded from further analysis.<sup>e</sup> Owing to lack of usable data, the rectus femoris (quadriceps) and biceps femoris (hamstring) muscle analyses were omitted.

The DC offset was removed from the EMG recordings, and then the signal was then rectified and filtered at 5Hz using a fourth order Butterworth low pass filter. The EMG data was then normalized temporally using the average stride time (using the same method described for the goniometers). The mean EMG output (in volts) was recorded. The muscle groups analyzed followed recognized response

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<sup>e</sup> See Appendix B to observe which sensors resulted in unusable data.

patterns; however, an occasional second peak in the gastrocnemius EMG data which does not typically occur in the literature occurred in several of the samples (9).



**Figure 4:** Prototypical EMG response for a subject's (top) tibialis anterior and (bottom) gastrocnemius muscles for a gait cycle. EMG output was normalized and overlaid, and the mean response is shown above.

### 3.4 Statistics

Student t-tests were performed to determine the likelihood of statistically significant differences in our results.<sup>f</sup> Various t-tests across appropriate subjects, legs, and loading conditions were performed for the different duration, kinematic, and muscle EMG gait parameters to determine statistical significance. The significance level was set at  $p = 0.05$  for all tests.

## 4. Results

### 4.1 Duration

Student t-tests between pairs of subjects showed that the differences in mean stride time between subjects' dominant legs in the unloaded condition were statistically significant. Attempts were made to

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<sup>f</sup> The author realizes that, in a complete study, Analysis of Variance (ANOVA) should be performed in order to effectively analyze across the multiple subjects and variables. However, due to timing constraints, ANOVA has been deferred to future work.

normalize and pool subject data using a number of scaling factors, but none succeeded. The factors explored were: 1) scaling according to subjects' height, 2) scaling according to the inverted pendulum frequency model ( $\sqrt{height}$ ), and 3) scaling according to Body Mass Index (BMI), where BMI is defined as:

$$BMI = \frac{m}{h^2} \quad (2)$$

where m is mass of the subject in kilograms and h is subject height in meters.

However, when comparing the mean stride duration between contralateral legs for both loaded and unloaded conditions, the t-tests failed to reject statistical equivalence. In fact, they actually produced high correlation values, with  $p = 0.9305$  as the lowest, and for the rest having  $p \geq 0.9704$ , indicating a high degree of similarity in stride duration times between contralateral legs.

T-tests between loaded and unloaded conditions for both dominant and non-dominant legs yielded significant variation for all subjects, conditions, and legs. While the trends were in opposite directions (Subjects 1 and 3 increased stride duration, while Subject 2 went down), they demonstrated a noteworthy increase in stride duration for subjects (see Table 2).

In order to use the peak ankle plantarflexion to predict toe-off, the temporal consistency of the ankle goniometers had to be ascertained. The mean coefficient of variation (COV) for the timing within each stride of the peak ankle plantarflexion (stance percent) resulted as  $COV = 0.034$ , which demonstrated very low variability in the t-test measurement, indicating the ankle goniometer's usefulness as a standard of temporal measurements. T-tests further showed significant differences between both the left and right foot and the loaded and unloaded condition for each subject. However, no trends can be seen in the mean stance time data between the loaded and unloaded condition.

The stance percent, as a normalized variable, had t-tests run between the different subjects. Most of the leg's stance percents returned with extremely significant differences

( $p \leq 2.79 \times 10^{-5}$ ). However, the dominant leg, in the loaded condition, returned much less significant differences, with p-values ranging from 0.0163 to 0.259. T-tests were also performed on the left and right legs and loaded and unloaded conditions and all resulted in statistically significant differences between the left and right legs. However, changes in the mean stance percent appeared similar to changes in stance durations, yielding no clear trends. While the SI did show statistically significant differences between each of the subjects, the mean COV for the SI measurements came to 0.729. In addition, despite the differences, the entire range of the mean SI was restricted from 0.648% to 1.98%, demonstrating a very low absolute change in the SI.

**TABLE 2: Mean Duration and Symmetry Parameters**

Subject /Condition	Leg	Duration			Symmetry	
		Stride Time	Stance Time	% Stance Time	SI	STD
Subject 1	Dom. Leg	1.17 sec	0.80 sec	68.12%	0.87%	0.65%
	Non-Dom. Leg	1.17 sec	0.78 sec	67.02%		
Subject 1 Loaded	Dom. Leg	1.23 sec	0.83 sec	67.14%	1.98%	1.21%
	Non-Dom. Leg	1.23 sec	0.77 sec	62.25%		
Subject 2	Dom. Leg	1.11 sec	0.77 sec	70.23%	1.42%	1.15%
	Non-Dom. Leg	1.11 sec	0.77 sec	69.67%		
Subject 2 Loaded	Dom. Leg	1.09 sec	0.74 sec	67.69%	1.65%	1.13%
	Non-Dom. Leg	1.09 sec	0.77 sec	70.93%		
Subject 3	Dom. Leg	1.19 sec	0.83 sec	69.35%	0.65%	0.49%
	Non-Dom. Leg	1.19 sec	0.82 sec	68.51%		
Subject 3 Loaded	Dom. Leg	1.27 sec	0.86 sec	67.30%	0.77%	0.59%
	Non-Dom. Leg	1.27 sec	0.85 sec	66.62%		

Finally, the contralateral heel strike mean values also came out to have statistically significant differences between the loaded and unloaded conditions for both the timing and percent of stance time ( $p \leq 0.0071$ ). While the time between heel strikes increased in the loaded condition for every subject, with some subjects showing significant time increases, the change in percent of stride fluctuated between subjects, increasing slightly for some while decreasing for others.

**TABLE3: Contralateral (Loaded/Unloaded) Heel Strike Timing**

Subject /Condition	Loaded/Unloaded Heel Strikes	% of Stride
Subject 1	0.59 sec	50.71%
Subject 1 Loaded	0.61 sec	49.20%
Subject 2	0.53 sec	47.86%
Subject 2 Loaded	0.54 sec	49.42%
Subject 3	0.60 sec	50.48%
Subject 3 Loaded	0.64 sec	50.71%

## **4.2 Kinematics**

The timing of the knee and ankle peak angles both produced distributions with surprisingly low variance, as the percent of gait cycle COV's were 0.039 and 0.034, respectively. As mentioned with calculation of stance time, these low COVs indicate the reliability of the goniometer measurements for the temporal aspects of the angle data.

The peak plantarflexion timing of the ankle was already described above (stance time and percent stance time). For the knee peak flexion angle, the time to maximum angle was compared for each loaded and unloaded subject, with a statistically significant difference being observed for each one. Percent of gait cycle till peak knee flexion was also compared across subjects, legs, and loading conditions with a t-test, resulting in statistically significant differences in the mean for each pairing. While the absolute value of the mean peak angle times vary in their response to loading, the timing of the peak knee flexion as a percent of the gait cycle drops noticeably from each non-loaded to loaded condition.



**TABLE 4: Peak Knee Flexion Timing**

Subject /Condition	Leg	Time Into Gait	Percent of Gait
Subject 1	Dom. Leg	0.88 sec	75.46%
	Non-Dom. Leg	0.87 sec	74.66%
Subject 1 Loaded	Dom. Leg	0.88 sec	71.35%
	Non-Dom. Leg	0.89 sec	72.13%
Subject 2	Dom. Leg	0.86 sec	78.20%
	Non-Dom. Leg	-	-
Subject 2 Loaded	Dom. Leg	0.82 sec	75.34%
	Non-Dom. Leg	-	-
Subject 3	Dom. Leg	0.89 sec	75.06%
	Non-Dom. Leg	0.91 sec	76.35%
Subject 3 Loaded	Dom. Leg	-	-
	Non-Dom. Leg	0.96 sec	75.90%

### 4.3 EMG Activity

Unlike the goniometer output, the COV values for the mean EMG per stride demonstrated a notable amount of variance, with an average COV = 0.30 for the tibialis anterior and an average COV = 0.32 for the gastrocnemius. Both the tibialis anterior and gastrocnemius were analyzed with t-tests between the loaded and unloaded conditions for each subject and leg. Significant statistical differences between each case were determined ( $p \leq 7.2 \times 10^{-7}$ ), except for Subject 2's non-dominant foot ( $p = 0.34$ ). This appears to be an unexplained anomaly but further work is required to establish that speculation. While the mean outputs all vary significantly, no clear trend can be seen in the data (see Table 5).

**TABLE 5: Mean EMG Output per Stride**

<b>Setup</b>		<b>Tibialis Anterior</b>	<b>Gastrocnemius</b>
<b>Subject /Condition</b>	<b>Leg</b>	<b>Mean EMG (V)</b>	<b>Mean EMG (V)</b>
Subject 1	Dom. Leg	1.79E-04	3.36E-05
	Non-Dom. Leg	1.92E-05	1.49E-05
Subject 1 Loaded	Dom. Leg	1.98E-05	8.15E-06
	Non-Dom. Leg	1.57E-05	1.18E-05
Subject 2	Dom. Leg	3.72E-05	2.60E-03
	Non-Dom. Leg	1.08E-05	2.40E-05
Subject 2 Loaded	Dom. Leg	6.45E-05	2.04E-05
	Non-Dom. Leg	1.78E-05	2.50E-05
Subject 3	Dom. Leg	1.97E-05	2.37E-05
	Non-Dom. Leg	1.49E-05	1.12E-05
Subject 3 Loaded	Dom. Leg	2.05E-05	1.95E-05
	Non-Dom. Leg	2.04E-05	1.89E-05

## 5. Conclusion

The results presented above demonstrated a clear change in the biomechanical response due to the loading of the system, especially in the gait duration data. In particular, the clear changes in stride durations, especially in Subjects 1 and 3, demonstrated the effects of the loading. While the results for Subject 2 differed for stride duration time, lengthening the duration instead of shortening it, a range of variables, such as height or sex, may account for this variation, and further study is required to ascertain the cause.

In contrast, the equivalence of duration for contralateral strides in both the loaded and unloaded condition points to a regulating mechanism to adjust one leg to the rhythm of the other. Clearly the ground's physical reaction forces play some role in keeping the mean stride times equal, but there also appears to be a neurological control system governing the behavior. In addition, the appearance of similarities in percent stance of the loaded leg between subjects may indicate an attempt by the neural controller to regulate aspects of the gait cycle, but this speculation remains unproven.

Moreover, exploration of the SI did not reveal any truly important differences under loading. While it is true that the SI increased in the loaded case for all subjects, the large COV of the SI and the

inherently low mean SI values made it difficult to claim a truly notable increase in asymmetry. However, the analysis of contralateral heel strikes showed a consistently small change in percent phase shift. This minimization of change is indicative of a mechanism that adjusts the relative timing of steps to keep walking cadences out of phase despite asymmetric lower limb loading.

While the data presented by kinematic and EMG analysis provided limited conclusions, one important note was the propensity for the peak knee flexion to shift to earlier in the gait cycle when under loading. This shift could correlate with the reduction in nonparetic peak knee flexion noted by Khanna et al. (7). An earlier peak in the knee cycle, rather than indicating a shift in the timing of the knee flexion, could also indicate a shortened activation of knee flexors, which would lead to a peak lower angle. In the current experiment, the subject's healthy range of motion would have allowed them to display the shortened knee flexion in both legs rather than just the nonparetic limb, as happened with Khanna et al.'s subjects.

In summary, it is clear that, regardless of the other biomechanical gait parameters, the body adjusts itself to minimize any temporal asymmetry it may experience under asymmetric loading.

## **6. Future Work**

While this preliminary study's results reveal several significant trends, most notably the temporal symmetry and control of the lower limb locomotion under loading, many further analysis techniques and experimental adjustments could be made to yield valuable further data.

One important change that will be crucial to pursue in future work is the change from multiple t-tests to ANOVA. ANOVA will prove more accurate than multiple t-tests in analyzing the data, as it will be able to better incorporate multiple populations. It will also be able to incorporate and deal with the multiple factors (loading, left and right leg) in a multiple factor ANOVA test. Finally, as an F-test ANOVA has the ability to differentiate between assignable and random causes between populations, an important factor in human biomechanics data.

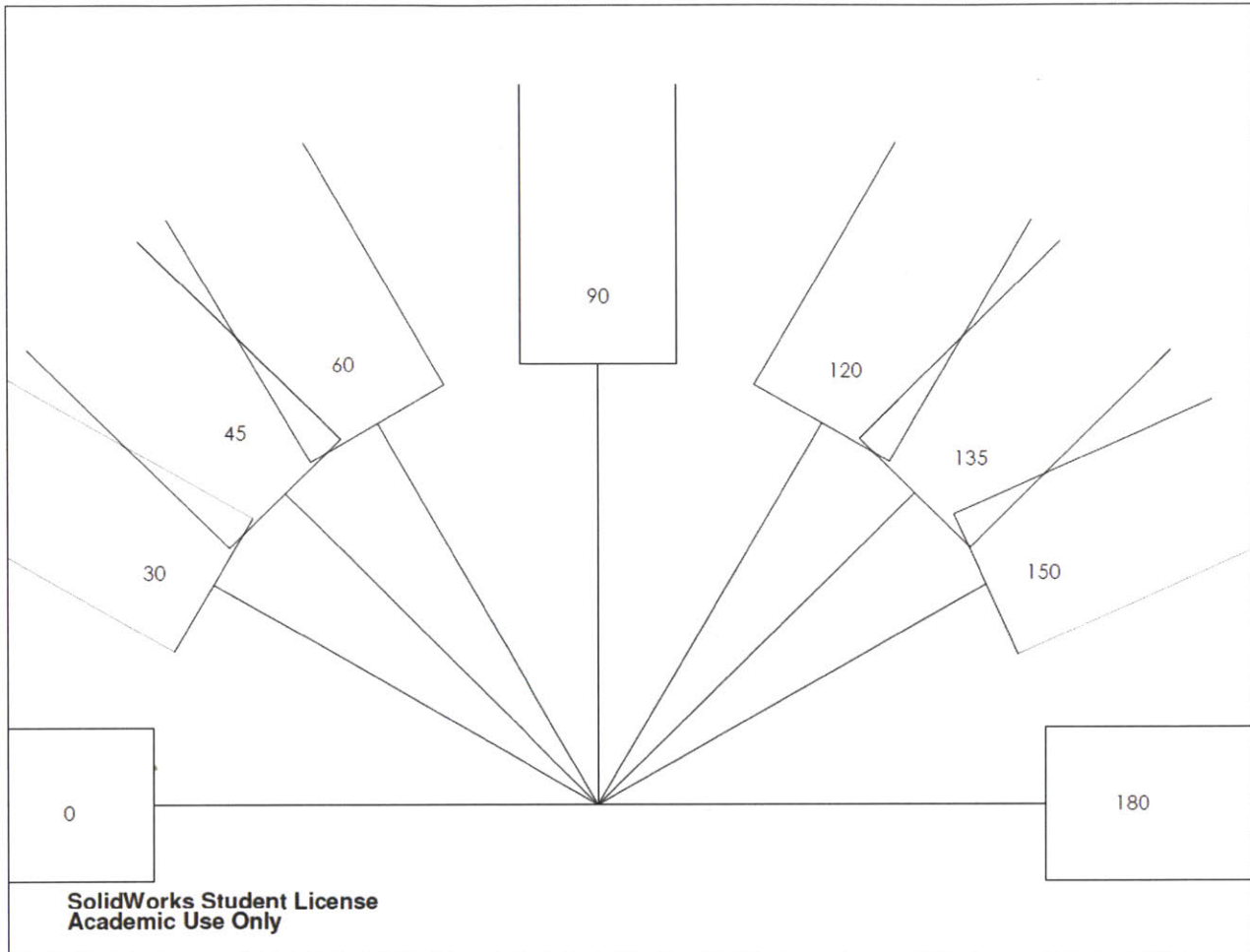
In addition, while the temporal data obtained in the current work is a start, the ability to measure knee and ankle angles is crucial to a better understanding of asymmetrically loaded walking. In order to do so, a more thorough knowledge of the current goniometers or new goniometers must be obtained. In particular, confirmation of Khanna et al.'s reported change in the nonparetic peak knee flexion and paretic knee dorsiflexion would be beneficial (7). This information, combined with goniometer confirmation of the temporal location of the beginning of knee flexion, would demonstrate whether or not the shift in knee flexion timing observed in the current experiment is indicative of an overall phase shift in knee flexion, or merely a shortening of the flexor muscle output. It would also reveal a great deal about the underlying strategies used to adjust to the heavier loads. In addition, a more accurate angular analysis of flexion and extension would help to confirm other limb trajectories affected by asymmetric loading.

Finally, this pilot test explored quadriceps and hamstring EMG placement and setup. The author recommends that further tests should build upon this paper's work, especially ensuring secure attachment of the sensors and routing of the cables, as later tests with a more refined system setup showed better results than earlier tests. The quadriceps placement should also be considered, as the results for the current experiment often led to frequencies indicative of an artifact. The information from these EMG sensors would do a great deal to illuminate the control strategy used to regulate lower limb walking in response to the loading—the changes or lack thereof in kinematics should be equally correlated with responses from the EMG output. Not only would EMG data be helpful for magnitude comparisons, but temporal analysis of muscle activation would illuminate certain timing aspects of the control.

## 7. Appendix

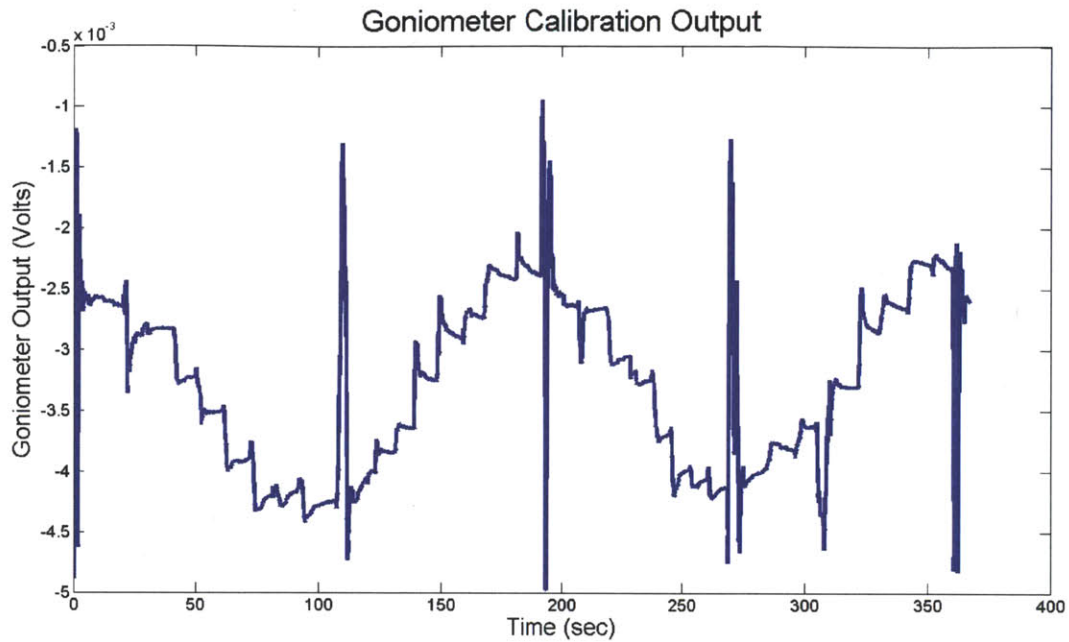
### Appendix A – Goniometer Calibration Methods

In order to calibrate the goniometers, a degree calibration sheet was made from SolidWorks® 2011 with angles from 30-180 degrees. The goniometer was positioned at each of the angles four times, and the voltage output from the goniometer was recorded through the calibration test. The outputs were recorded through the DelsysMyomonitor® system.



**Figure 5:** The goniometers were calibrated by moving the goniometers along the angle pattern sheet.

Both directions of flexion on the goniometer were calibrated separately. The voltage output results were fit in MATLAB using the POLYFIT function. Unfortunately, the goniometers became unreliable near the 30 and 180 degrees limits, as well as being imprecise throughout the entire goniometer range.



**Figure 6:** Sample goniometer calibration voltage output. The goniometer was traced back and forth on the SolidWorks® calibration sheet twice to obtain the calibration data points.



**Figure 7:** The goniometer. The positioning of the ID numbers (lower left hand block) was used as the reference for the direction of the goniometer. The double sided mounting tape can be seen on the upper right block.

## Appendix B– Usable Data

**TABLE 6: Usable Data**

TABLE 1. SUBJECT 1				
	Unloaded Dom	Unloaded Non-Dom	Loaded Dom	Loaded Non-Dom
Knee Gonio	Good	Good	Good	Good
Ankle Gonio	Good ""	Good ""	Good ""	Good ""
Quad EMG	Bad	Bad	Bad	Bad
Ham EMG	Bad	Good ""	Good ""	Good ""
TA EMG	Good ""	Good ""	Good ""	Good ""
Gastro EMG	Bad	Good ""	Good ""	Good ""
Heel Switch	Good	Good	Good	Good
Subject 2				
	Unloaded Dom	Unloaded Non-Dom	Loaded Dom***	Loaded Non-Dom***
Knee Gonio	Good	Bad	Good	Bad
Ankle Gonio	Good ""	Good	Good	Good
Quad EMG	Bad	Bad	Bad	Bad
Ham EMG	Bad	Bad	Bad	Bad
TA EMG	Good ""	Good	Bad	Good
Gastro EMG	Bad	Good	Bad	Good
Heel Switch	Good**	Good	Good**	Good
Subject 3				
	Unloaded Dom	Unloaded Non-Dom	Loaded Dom	Loaded Non-Dom
Knee Gonio	Good	Good	Bad	Good ""
Ankle Gonio	Good ""	Good	Good	Good
Quad EMG	Bad	Good ""	Good	Bad
Ham EMG	Good ""	Good ""	Bad	Bad
TA EMG	Good	Good ""	Good	Good
Gastro EMG	Good	Good ""	Good	Good
Heel Switch	Good	Good	Good	Good
Good	Indicates good reading			
Bad	Indicates bad reading			
Good ""	Indicates needed to remove random spikes			
**Subject 2's dominant leg has weird peaks in the heel strike data, causing large deviations in spread				
***Subject 2's loaded trial only lasted for a bit over 5 min				

## Appendix C– Sample Code for Data Processing

### Sample Code For Subject 1 in the Unloaded Trial

```
dat = subldat;
%%
subnum = 'sub1';
%%

enddat = 600000;
halfdat = 300000;

%Removing spikes from data
%optional - dedends on data*****
%dom ankle
remove = dat(:,3);
remove(remove < -.0038) = -.00344;
dat(:,3) = remove;

%non-dom ankle
remove = dat(:,10);
remove(remove < -.00406) = -.0038;
dat(:,10) = remove;

%dom TA
remove = dat(:,6);
remove(remove > .0006 & remove<-.0008 ) = mean(remove);
dat(:,6) = remove;

%non-dom Ham
remove = dat(:,12);
remove(remove > .0003 & remove<-.0003 ) = mean(remove);
dat(:,12) = remove;

%non-dom TA
remove = dat(:,13);
remove(remove > .0004 & remove<-.0005 ) = mean(remove);
dat(:,13) = remove;

%non-dom Gastro
remove = dat(:,14);
remove(remove > .0002 & remove<-.0004 ) = mean(remove);
dat(:,14) = remove;

%Goniometers - volts to degrees. Infor comes from calibratoin script
%check to insure correct orientation of goniometer
figure(1);
    t= dat(:,1);
%Knee Dominant.
subplot(2,2,1);
    w = dat(:,2);
dat(:,2) = 1.0e+008*(4.020751325121656*w.^3 -0.007183393503045*w.^2 + -
0.000431669254195*w.^1 + 0.000000968179196);
```



```
plot(t(300001:310000), 1.0e+008 *(4.020751325121656*w(300001:310000).^3 -
0.007183393503045*w(300001:310000).^2 + 0.000431669254195*w(300001:310000).^1
+ 0.000000968179196));
```

```
%Ankle Dom.
```

```
subplot(2,2,2);
x = dat(:,3);
dat(:,3) = 1.0e+005 *(-6.796266001448857*x.^2 + 0.463210635990114*x+
0.002134919571317);
plot(t(300001:310000), 1.0e+005 *(-6.796266001448857*x(300001:310000).^2 +
0.463210635990114*x(300001:310000)+ 0.002134919571317));
```

```
%Knee Alt.
```

```
subplot(2,2,3);
z = dat(:,9);
dat(:,9) = 1.0e+010 *(-1.636709553700273*z.^3 -0.009902638748577*z.^2 -
0.000026756956310*z -0.000000015382608);
plot(t(300001:310000), 1.0e+010 *(-1.636709553700273*z(300001:310000).^3 -
0.009902638748577*z(300001:310000).^2 -0.000026756956310*z(300001:310000) -
0.000000015382608));
```

```
%Ankle Alt.
```

```
subplot(2,2,4);
y = dat(:,10);
dat(:,10) = 1.0e+009 *(-3.257033868770031*y.^3 -0.042575152240692*y.^2 -
0.000121964934110*y +0.000000083224399);
plot(t(300001:310000), 1.0e+009 *(-3.257033868770031*y(300001:310000).^3 -
0.042575152240692*y(300001:310000).^2 -0.000121964934110*y(300001:310000)
+0.000000083224399));
```

```
%Leg1
```

```
%Calculating average stride time
```

```
%Locating footswitch data
```

```
%locating peaks on footswitch
```

```
%unloaded - we want just the values from 300sec onward, really.
```

```
[maga, loca] = findpeaks(dat(:,8), 'MINPEAKDISTANCE', 1000);
```

```
mag = maga(2:(length(maga)));
```

```
%check
```

```
if need this for peak heel before heel strike
```

```
loc = loca(2:(length(loca)));
```

```
%
```

```
%find heel strike locations - it assumes set magnitude of for
```

```
%start of heel strike - may change
```

```
relheelswitch = dat(1:enddat,8);
```

```
peak_beginnings = zeros(size(loc));
```

```
pb_height = zeros(size(loc));
```

```
fori=1:length(loc)
```

```
height = mag(i);
```

```
j=0;
```

```
while height > .00031
```

```
%%%%%%changes per subject
```

```
j=j+1;
```

```
height = relheelswitch(loc(i)-j);
```

```

end
peak_beginnings(i)=loc(i)-j;
pb_height(i) = dat(peak_beginnings(i), 8);
end

%calculate the number of strides
numstrides = length(mag)-1;

%stride time - actual times and location of times
stridettime = diff(dat(loc,1));
stridettimeLoc = diff(loc);
meanstridettimeLoc = mean(stridettimeLoc);
meanstridettime = mean(stridettime);
medianstridettimeLoc = median(stridettimeLoc);
medianstridettime = median(stridettime);
usestridettime = round(meanstridettimeLoc); %notice that this is the data
index length of stride time, not the actual stride time itself, which will be
off by about .0022 per stride length

%heel strike - this is the location of the time index, not the time- we care
about
%the location to call for overlay later
heelstridet = diff(peak_beginnings);
mean(heelstridet);

halfheelLoc = find(dat(peak_beginnings,1)>300,1);
halfheeltime = peak_beginnings(halfheelLoc);

stridettimebeg = stridettime(1:(halfheelLoc));
meanstridettimebeg = mean(stridettimebeg);
stridettimeend = stridettime(halfheelLoc:length(stridettime));
meanstridettimeend = mean(stridettimeend);

%plot - distribution of time
figure(2)

%whole thing
histobox = (round(min(stridettime)):.001:(round(max(stridettime))+.6));
%%check borders of histogram per subject
subplot(1,3,1)
hist(stridettime, histobox);

%first half
histobox = (round(min(stridettime)):.001:(round(max(stridettime))+.6));
%%check borders of histogram per subject
subplot(1,3,2)
hist(stridettime(1:(halfheelLoc-1)), histobox);

title([subnum'_leg1'_ '_distribution of stridettime'])

%second half

```

```

histobox = (round(min(stridetime)):.001:(round(max(stridetime))+.6);
%%check borders of histogram per subject
subplot(1,3,3)
hist(stridetime(halfheelloc:length(stridetime)), histobox);

%%
%plot stridetime
figure(3)

%full
subplot(1,3,1);
t = 1:length(stridetime);
plot(t, stridetime, 'b');

%beg
subplot(1,3,2);
t = 1:(halfheelloc-1);
stridetimebeg = stridetime(1:(halfheelloc-1));
plot(t, stridetimebeg);

title([subnum'_leg1_'_stridetime'])

%end
subplot(1,3,3);
t = (halfheelloc):length(stridetime);
stridetimeend = stridetime((halfheelloc):length(stridetime));
plot(t, stridetimeend);
%%
%plot heelstridetime and heelstrikes
figure(4)

subplot(2,1,1);

title([subnum'_leg1_'_heelstrike'])

plot(heelstridet)

subplot(2,1,2);
plot( dat(1:length(dat),1), dat(1:length(dat),8), 'b',
dat((peak_beginnings(1:length(pb_height))),1),
pb_height(1:(length(pb_height))), 'r*')

%rectify and filter EMG data
%unloaded
fori = 4:7;
dat(:,i) = Butter4_Low_Pass_Filter(abs(dat(:,i))-mean(dat(:,i))), 1000, 5);
end

%overlay
%average data set for subject
%prep matrix for subject average data
avealldata = zeros(usesstridetime,15);
avealldatabeg = zeros(usesstridetime,15);

```

```

avealldataend = zeros(usestridetime,15);
%first column is time
avealldata(:,1) = dat(1:usestridetime, 1);
avealldatabeg(:,1) = dat(1:usestridetime, 1);
avealldataend(:,1) = dat(1:usestridetime, 1);

for j = 2:8;
%single vector for subject
%prep matrix for vector
    sumlvectordata = zeros((numstrides),usestridetime);

%call data - except last one because of end effect of
%resample

% first stride
callstrideextra =
dat(((peak_beginnings(1))):((peak_beginnings(1))+2*heelstridet(1) - 1),j);
callstridenorm = resample(callstrideextra, (usestridetime-1),
(heelstridet(numstrides)-1));
callstrideuse = callstridenorm(1:(usestridetime));
sumlvectordata(1,:) = callstrideuse';

fori = 2:(numstrides-1)
callstrideextra = dat(((peak_beginnings(i))+ (1 -
heelstridet(i))):((peak_beginnings(i))+2*heelstridet(i) - 1),j);

size(callstrideextra);
callstridenorm = resample(callstrideextra, (usestridetime-1),
(heelstridet(i)-1));
size(callstridenorm);
callstrideuse = callstridenorm((usestridetime):(2*usestridetime-1));
size(callstrideuse');
size(sumlvectordata);

sumlvectordata(i,:) = callstrideuse';
end
% last stride
callstrideextra = dat(((peak_beginnings(numstrides))+ (1 -
heelstridet(numstrides))):length(dat),j);
callstridenorm = resample(callstrideextra, (usestridetime-1),
(heelstridet(numstrides)-1));
callstrideuse = callstridenorm((usestridetime):(2*usestridetime-1));
sumlvectordata(numstrides,:) = callstrideuse';

%split to first half and last half
    sumlvectordatabeg = sumlvectordata(1:(halfheelloc-1),:);
    sumlvectordataend = sumlvectordata(halfheelloc:numstrides,:);

%turn into one average stride
aveallstride = sum(sumlvectordata)/numstrides;
aveallstridebeg = sum(sumlvectordatabeg)/(halfheelloc-1);
aveallstrideend = sum(sumlvectordataend)/(numstrides-halfheelloc+1);

%correct for angle on knee

```

```

if j == 2
depend on the front back orientation of the goniometer*****
%%these

allkneenorm = sumlvectordata;

aveallstride = -aveallstride + max(aveallstride);
aveallstridebeg = -aveallstridebeg + max(aveallstridebeg);
aveallstrideend = -aveallstrideend + max(aveallstrideend);
end
%correct for angle on ankle
if j == 3
depend on the front back orientation of the goniometer*****
%%these
allanklenorm = sumlvectordata;
%
allanklenormbeg = sumlvectordatabeg;
%
allanklenormend = sumlvectordataend;

aveallstride = -aveallstride + aveallstride(1);
aveallstridebeg = -aveallstridebeg + aveallstridebeg(1);
aveallstrideend = -aveallstrideend + aveallstrideend(1);

end

if j == 6;
allta = sumlvectordata;
meantavals = mean(allta, 2);
meantagait = mean(allta);

end

if j == 7;
allgastroc = sumlvectordata;
meangastrocvals = mean(allgastroc, 2);
meangastrocgait = mean(allgastroc);
end

figure(j+3);
subplot(2,1,1);
title([subnum'_leg1_'])
plot(dat((1:usestridetime), 1), aveallstride, 'b',
dat((1:usestridetime), 1), aveallstridebeg, 'g', dat((1:usestridetime), 1),
aveallstrideend, 'c', dat((1:(usestridetime)), 1),
dat((halfheeltime):(halfheeltime+ usestridetime-1)), j), 'r');
subplot(2,1,2);
hold on
for n = 1:(halfheelloc-1);
plot(1:usestridetime, sumlvectordatabeg(n,:), 'b');
end
for n = (halfheelloc:numstrides)-halfheelloc+1;
plot(1:usestridetime, sumlvectordataend(n,:), 'r');
end
hold off

%add to all vectors

avealldata(:,j) = aveallstride;

```

```

avealldatabeg(:,j) = aveallstridebeg;
avealldataend(:,j) = aveallstrideend;
end

figure(100)
holdon
for j = 2:3
plot(avealldata(:,1), avealldata(:,j),'b')
end
plot(avealldata(:,1), avealldata(:,4)*2000000,'r')
plot(avealldata(:,1), avealldata(:,5)*3000000,'y')
plot(avealldata(:,1), avealldata(:,6)*1000000,'g')
plot(avealldata(:,1), avealldata(:,7)*1000000,'c')
plot(avealldata(:,1), avealldata(:,8)*100000,'k')
title([subnum'_leg1'_ '_overlay all'])
holdoff

%Find toe-off point
[maganknorm, locanknorm] = max(allanklenorm(:,500:900), [], 2);
%double check the bound numbers for each stride - should be
similar.*****
locanknorm = locanknorm+500;
%re-add the stride location
maganknorm = maganknorm';
locanknorm = locanknorm';

% locanknormbeg = locanknorm(1:(halfheelloc-1));
% locanknormend = locanknorm(halfheelloc:length(locanknorm));

figure(12)
subplot(1,2,1);
title([subnum'_leg1'_ '_toe-strike check'])
plot(1:numstrides, locanknorm);
histboxtoe = (round(min(locanknorm)-1):(round(max(locanknorm))+1);
%*****each histobox will be different
subplot(1,2,2);
hist(locanknorm, histboxtoe);

%Since small variance in location of ankle output.
%Take raw data and overlay it, un-normalized.
%prep matrix for vector
    sumlankldata = zeros(numstrides, usestridetime);
fori = 1:(numstrides);
    sumlankldata(i,:) =
    dat(((peak_beginnings(i)):(peak_beginnings(i)+usestridetime-1)), 3)';
end
    [magank, locank] = max(sumlankldata(:,600:900), [], 2);
%***sub 1 calls the wrong data twice, because of the second spike being
higher.
magank = magank';
locank = locank+600;
locank = locank';
%locank are the locations of the toeoffs (locank(i)+300000)
%need to find stance time - have toe-off and heel-strike.

stancetimes = zeros(numstrides,1);

```

```

fori = 1:numstrides;
stancetimes(i) = dat((peak_beginnings(i)+locank(i)),1)-
dat((peak_beginnings(i)), 1);
end

stancetimesbeg = stancetimes(1:(halfheelloc-1));
stancetimesend = stancetimes(halfheelloc:numstrides);

figure(50)
subplot(1,2,1);
title([subnum'_leg1'_stancetimes all ''])
plot(1:length(stancetimes), stancetimes);
histboxtoe = (round(min(stancetimes))-0.5):.001:(round(max(stancetimes))-0.1);
%*****each histobox will be different
subplot(1,2,2);
hist(stancetimes, histboxtoe);

figure(51)
title([subnum'_leg1'_begendstancetimes'])
histboxbeg = (round(min(stancetimesbeg))-0.5):.001:(round(max(stancetimesbeg))-0.1);
histboxend = (round(min(stancetimesend))-0.5):.001:(round(max(stancetimesend))-0.1);
subplot(1,2,1);
hist(stancetimesbeg, histboxbeg);
subplot(1,2,2);
hist(stancetimesend, histboxend);
%%
figure(52)

allkneenormplot = zeros(size(sumlvectordata));
allanklenormplot = zeros(size(sumlvectordata));

fori = 1:numstrides;
allkneenormplot(i,:) = - allkneenorm(i,:) + max(allkneenorm(i,:));
allanklenormplot(i,:) = -allanklenorm(i,:) + (allanklenorm(i,1));
end
plot(allanklenormplot', allkneenormplot');
title([subnum'_leg1'_ankleknee'])

%Take raw data and overlay it, un-normalized.
%prep matrix for vector
sumlkneedata = zeros(numstrides,usestridetime);
fori = 1:(numstrides);
sumlkneedata(i,:) =
dat(((peak_beginnings(i)):(peak_beginnings(i)+usestridetime-1)),2)';
end
[magknee, locknee] = max(abs(sumlkneedata(:,600:1100)), [], 2);
%***sub 1 calls the wrong data twice, because of the second spike being
higher.
magknee = magknee';
locknee = locknee+600;
locknee = locknee';
%locknee are the locations of the toeoffs (locknee(i)+300000)
%need to find stance time - have toe-off and heel-strike.

```

```

kneeflextimes = zeros(numstrides,1);
fori = 1:numstrides;
kneeflextimes(i) = dat((peak_beginnings(i)+locknee(i)),1)-
dat((peak_beginnings(i)), 1);
end

%%
%non-dominant leg*****
%Calculating average stride time
%Locating footswitch data
%locating peaks on footswitch
%unloaded - we want just the values from 300sec onward, really.
[mag2,loc2] = findpeaks(dat(:,15), 'MINPEAKDISTANCE', 1000);

%find heel strike locations - it assumes set magnitude of for
%start of heel strike - may change
relheelswitch2 = dat(1:enddat,15);
peak_beginnings2 = zeros(size(loc2));
pb_height2 = zeros(size(loc2));
fori=1:length(loc2)
height = mag2(i);
j=0;
while height > .00029 %%%%%changes per subject
j=j+1;
height = relheelswitch2(loc2(i)-j);
end
peak_beginnings2(i)=loc2(i)-j;
pb_height2(i) = dat(peak_beginnings2(i), 15);
end

%calculate the number of strides
numstrides2 = length(mag2)-1;

%stride time - actual times and location of times
stridettime2 = diff(dat(loc2,1));
stridettime2loc2 = diff(loc2);
meanstridettime2loc2 = mean(stridettime2loc2);
meanstridettime2 = mean(stridettime2);
medianstridettime2loc2 = median(stridettime2loc2);
medianstridettime2 = median(stridettime2);
usestridettime2 = round(meanstridettime2loc2); %notice that this is the
data index length of stride time, not the actual stride time itself, which
will be off by about .0022 per stride length

%heel strike - this is the location of the time index, not the time- we care
about
%the location to call for overlay later
heelstridet2 = diff(peak_beginnings2);
mean(heelstridet2);

halfheelloc2 = find(dat(peak_beginnings2,1)>300,1);

```



```

halfheeltime2 = peak_beginnings2(halfheelloc2);

stridetimebeg2 = stridetime2(1:(halfheelloc2));
meanstridetimebeg2 = mean(stridetimebeg2);
stridetimeend2 = stridetime2(halfheelloc2:length(stridetime2));
meanstridetimeend2 = mean(stridetimeend2);

%plot - distribution of stridetime
figure(13)
%whole thing
histobox2 =
(round(min(stridetime2)):.001:(round(max(stridetime2))+.6);    %%%check
borders of histogram per subject
subplot(1,3,1)
hist(stridetime2, histobox2);

%first half
histobox2 =
(round(min(stridetime2)):.001:(round(max(stridetime2))+.6);    %%%check
borders of histogram per subject
subplot(1,3,2)
hist(stridetime2(1:(halfheelloc2-1)), histobox2);

title([subnum'_leg2_'distr. of stridetime'])

%second half
histobox2 =
(round(min(stridetime2)):.001:(round(max(stridetime2))+.6);    %%%check
borders of histogram per subject
subplot(1,3,3)
hist(stridetime2(halfheelloc2:length(stridetime2)), histobox2);

%plot stridetime
figure(14)

%full
subplot(1,3,1);
t2 = 1:length(stridetime2);
plot(t2, stridetime2, 'b');

%beg
subplot(1,3,2);
t2 = 1:(halfheelloc2-1);
stridetimebeg2 = stridetime2(1:(halfheelloc2-1));
plot(t2, stridetimebeg2);

title([subnum'_leg2_'_stridetines'])

%end
subplot(1,3,3);
t2 = (halfheelloc2):length(stridetime2);
stridetimeend2 = stridetime2((halfheelloc2):length(stridetime2));
plot(t2, stridetimeend2);

```

```

%plot heelstridettime and heelstrikes
figure(15)

subplot(2,1,1);
plot(heelstridet2)
title([subnum'_leg2_' '_heelstridet and strikes'])
subplot(2,1,2);
    plot( dat(1:length(dat),1), dat(1:length(dat),15), 'b',
dat((peak_beginnings2(1:length(pb_height2))),1),
pb_height2(1:(length(pb_height2))), 'r*')

%rectify and filter EMG data
%unloaded
fori = 11:14;
dat(:,i) = Butter4_Low_Pass_Filter(abs(dat(:,i))-mean(dat(:,i))), 1000, 5);
end

%overlay
%average data set for subject
%prep matrix for subject average data
%%
for j = 9:15;
%single vector for subject
%prep matrix for vector
    sumlvectordata2 = zeros((numstrides2),usestridettime2);

%call data - except last one because of end effect of
%resample

% first stride
    callstrideextra2 =
dat(((peak_beginnings2(1))):((peak_beginnings2(1))+2*heelstridet2(1) - 1),j);
    callstridenorm2 = resample(callstrideextra2, (usestridettime2-
1), (heelstridet2(numstrides2)-1));
    callstrideuse2 = callstridenorm2(1:(usestridettime2));
sumlvectordata2(1,:) = callstrideuse2';

fori = 2:(numstrides2-1)
    callstrideextra2 = dat(((peak_beginnings2(i))+ (1 -
heelstridet2(i))):((peak_beginnings2(i))+2*heelstridet2(i) - 1),j);

size(callstrideextra2);
    callstridenorm2 = resample(callstrideextra2,
(usestridettime2-1), (heelstridet2(i)-1));
size(callstridenorm2);
    callstrideuse2 =
callstridenorm2((usestridettime2):(2*usestridettime2-1));
size(callstrideuse2');
size(sumlvectordata2);

sumlvectordata2(i,:) = callstrideuse2';
end
% last stride

```

```

        callstrideextra2 = dat(((peak_beginnings2(numstrides2))+ (1 -
heelstridet2(numstrides2)))):length(dat),j);
        callstridenorm2 = resample(callstrideextra2, (usestridet2-
1), (heelstridet2(numstrides2)-1));
        callstrideuse2 =
callstridenorm2((usestridet2):(2*usestridet2-1));
sumlvectordata2(numstrides2,:) = callstrideuse2';

%split to first half and last half
        sumlvectordatabeg2 = sumlvectordata2(1:(halfheelloc2-1),:);
        sumlvectordataend2 =
sumlvectordata2(halfheelloc2:numstrides2,:);

%turn into one average stride
        aveallstride2 = sum(sumlvectordata2)/numstrides2;
        aveallstridebeg2 = sum(sumlvectordatabeg2)/(halfheelloc2-1);
        aveallstrideend2 = sum(sumlvectordataend2)/(numstrides2-
halfheelloc2+1);

%correct for angle on knee
if j == 9 %%%these
depend on the front back orientation of the goniometer*****

        allkneenorm2 = sumlvectordata2;

        aveallstride2 = -aveallstride2 + max(aveallstride2);
        aveallstridebeg2 = -aveallstridebeg2 +
max(aveallstridebeg2);
        aveallstrideend2 = -aveallstrideend2 +
max(aveallstrideend2);

end
%correct for angle on ankle
if j == 10

        allanklenorm2 = sumlvectordata2;
        %
        allanklenormbeg = sumlvectordatabeg;
        %
        allanklenormend = sumlvectordataend;

        aveallstride2 = -aveallstride2 + aveallstride2(1);
        aveallstridebeg2 = -aveallstridebeg2 +
aveallstridebeg2(1);
        aveallstrideend2 = -aveallstrideend2 +
aveallstrideend2(1);

end

if j == 13;

        allta2 = sumlvectordata2;
        meantavals2 = mean(allta2, 2);
        meantagait2 = mean(allta2);

end

if j == 14;

        allgastroc2 = sumlvectordata2;

```

```

        meangastrocvals2 = mean(allgastroc2, 2);
        meangastrocgait2 = mean(allgastroc2);

end

figure(j+7);
subplot(2,1,1);
        plot(dat((1:usestridetime2), 1), aveallstride2,'b',
dat((1:usestridetime2), 1), aveallstridebeg2,'g',dat((1:usestridetime2), 1),
aveallstrideend2,'c', dat((1:(usestridetime2)),1),
dat((halfheeltime2):(halfheeltime2+ usestridetime2-1)),j),'r');
subplot(2,1,2);
holdon
for n = 1:(halfheelloc2-1);
plot(1:usestridetime2, sumlvectordatabeg2(n,:), 'b');
end
for n = (halfheelloc2:numstrides2)-halfheelloc2+1;
plot(1:usestridetime2, sumlvectordataend2(n,:), 'r');
end
holdoff

%add to all vectors

avealldata(:,j) = aveallstride2;
avealldatabeg(:,j) = aveallstridebeg2;
avealldataend(:,j) = aveallstrideend2;
end

figure(23)
holdon
for j = 9:10
plot(avealldata(:,1), avealldata(:,j), 'b')
end
plot(avealldata(:,1), avealldata(:,11)*2000000, 'r')
plot(avealldata(:,1), avealldata(:,12)*3000000, 'y')
plot(avealldata(:,1), avealldata(:,13)*1000000, 'g')
plot(avealldata(:,1), avealldata(:,14)*1000000, 'c')
plot(avealldata(:,1), avealldata(:,15)*100000, 'k')
title([subnum'_leg2_'_overlay all '])
holdoff
%%
%Find toe-off point
[maganknorm2, locanknorm2] = max(allanklenorm2(:,500:850), [], 2);
%double check the bound numbers for each stride - should be
similar.*****
locanknorm2 = locanknorm2+500;
maganknorm2 = maganknorm2';
locanknorm2 = locanknorm2';

% locanknormbeg = locanknorm(1:(halfheelloc-1));
% locanknormend = locanknorm(halfheelloc:length(locanknorm));

figure(24)
subplot(1,2,1);
plot(1:numstrides2, locanknorm2);

```

```

title([subnum'_leg2'_ '_test ankle loc'])

histboxtoe2 = (round(min(locanknorm2)-1):(round(max(locanknorm2))+1);
%*****each histobox will be different
subplot(1,2,2);
hist(locanknorm2, histboxtoe2);

%Since small variace in location of ankle output.
%Take raw data and overlay it, un-normalized.
%prep matrix for vector
    sumlankledata2 = zeros(numstrides2,usestridetime2);
fori = 1:(numstrides2);
sumlankledata2(i,:) =
dat(((peak_beginnings2(i)):(peak_beginnings2(i)+usestridetime2-1)),10)';
end
    [magank2, locank2] = max(sumlankledata2(:,600:850), [], 2);
%***sub 1 calls the wrong data twice, because of the second spike being
higher.
    magank2 = magank2';
    locank2 = locank2+600;
    locank2 = locank2';
%locank are the locations of the toeoffs (locank(i)+300000)
%need to find stance time - have toe-off and heel-strike.

stancetimes2 = zeros(numstrides2,1);
fori = 1:numstrides2;
stancetimes2(i) = dat((peak_beginnings2(i)+locank2(i)),1)-
dat((peak_beginnings2(i)), 1);
end

stancetimesbeg2 = stancetimes2(1:(halfheelloc2-1));
stancetimesend2 = stancetimes2(halfheelloc2:numstrides2);

figure(60)
subplot(1,2,1);
plot(1:length(stancetimes2), stancetimes2);

title([subnum'_leg2'_ '_stancetimes all'])

histboxtoe2 = (round(min(stancetimes2))-0.3):.001:(round(max(stancetimes2))-
.1);
%*****each histobox will be different
subplot(1,2,2);
hist(stancetimes2, histboxtoe2);

figure(61)
histboxbeg2 = (round(min(stancetimesbeg2))-
.3):.001:(round(max(stancetimesbeg2))-0.1);
histboxend2 = (round(min(stancetimesend2))-
.3):.001:(round(max(stancetimesend2))-0.1);
subplot(1,2,1);
hist(stancetimesbeg2, histboxbeg2);
title([subnum'_leg2'_ '_begend stance times'])

subplot(1,2,2);
hist(stancetimesend2, histboxend2);

```

```

%%
figure(62)

allkneenormplot2 = zeros(size(sum1vectordata2));
allanklenormplot2 = zeros(size(sum1vectordata2));

fori = 1:numstrides2;
allkneenormplot2(i,:) = - allkneenorm2(i,:) + max(allkneenorm2(i,:));
allanklenormplot2(i,:) = -allanklenorm2(i,:) + (allanklenorm2(i,1));
end

plot(allanklenormplot2', allkneenormplot2');
title([subnum'_leg2_'_ankle'knee'])

%Take raw data and overlay it, un-normalized - knee data.
%prep matrix for vector
    sum1kneedata2 = zeros(numstrides2,usestridetime2);
fori = 1:(numstrides2);
sum1kneedata2(i,:) =
dat(((peak_beginnings2(i)):(peak_beginnings2(i)+usestridetime2-1)),9)';

end
holdoff
    [magknee2, locknee2] = min(abs(sum1kneedata2(:,600:1100)), [],
2);
    %***sub 1 calls the wrong data twice, because of the second
spike being higher.
    magknee2 = magknee2';
    locknee2 = locknee2+600;
    locknee2 = locknee2';
%locknee are the locations of the max knee flexion(locknee(i)+300000)
%need to find stance time - have toe-off and heel-strike.

kneeflextimes2 = zeros(numstrides2,1);
fori = 1:numstrides2;
kneeflextimes2(i) = dat((peak_beginnings2(i)+locknee2(i)),1)-
dat((peak_beginnings2(i)), 1);
end

%%
%compute important data
meanstancetimes = mean(stancetimes);
meanstancetimesbeg = mean(stancetimesbeg);
meanstancetimesend = mean(stancetimesend);
    meanstancetimes2 = mean(stancetimes2);
    meanstancetimesbeg2 = mean(stancetimesbeg2);
    meanstancetimesend2 = mean(stancetimesend2);

meanall = mean(avealldata);
highpeakall = max(avealldata);
lowpeakall = min(avealldata);

impdat = [meanall; highpeakall; lowpeakall];

```

```

%mean symmetry
    vlmean = meanstancetimes/meanstridetime;
percent of gait cycle dominant (or loaded) leg
    v2mean = meanstancetimes2/meanstridetime2;
percent of gait cycle dominant leg
simean = 0.5*abs((vlmean-v2mean)/(vlmean+v2mean));

    vlmeanbeg = meanstancetimesbeg/meanstridetimebeg;
%stance percent of gait cycle dominant (or loaded) leg
    v2meanbeg = meanstancetimesbeg2/meanstridetimebeg2;
%stance percent of gait cycle dominant leg
simeanbeg = 0.5*abs((vlmeanbeg-v2meanbeg)/(vlmeanbeg+v2meanbeg));

    vlmeanend = meanstancetimesend/meanstridetimeend;
%stance percent of gait cycle dominant (or loaded) leg
    v2meanend = meanstancetimesend2/meanstridetimeend2;
%stance percent of gait cycle dominant leg
simeanend = 0.5*abs((vlmeanend-v2meanend)/(vlmeanend+v2meanend));

%running symmetry

    v1 = stancetimes./stridetime;
    v2 = stancetimes2./stridetime2;
    v2 = v2(2:(length(v2)-1));
%%change subldat to make steps the same for symmetry.
si = 0.5*abs((v1-v2)./(v1+v2));

    vlbeg = v1(1:(halfheelloc-1));
    vlend = v1(halfheelloc:length(v1));

    v2beg = v2(1:(halfheelloc-1));
    v2end = v2(halfheelloc:length(v2));

sibeg = si(1:(halfheelloc-1));
siend = si(halfheelloc:length(si));

figure(25)
title([subnum'---'_si v1 and v2'])
plot(1:length(stridetime), si, 1:length(stridetime), v1,
1:length(stridetime), v2);

figure(26)
histbox = (round(min(si))-0.1):.001:(round(max(si))+0.1);
histboxbeg = (round(min(sibeg))-0.1):.001:(round(max(sibeg))+0.1);
histboxend = (round(min(siend))-0.1):.001:(round(max(siend))+0.1);
subplot(1,3,1);
hist(si, histbox);
subplot(1,3,2);
hist(sibeg, histboxbeg);
title([subnum'---'_allbegendsi distribution'])
subplot(1,3,3);

```

```

hist(siend, histboxend);

figure(27)
histbox = (round(min(v1))-0.4):.001:(round(max(v1))-0.2);
histboxbeg = (round(min(v1beg))-0.4):.001:(round(max(v1beg))-0.2);
histboxend = (round(min(v1end))-0.4):.001:(round(max(v1end))-0.2);
subplot(2,3,1);
hist(v1, histbox);
title([subnum'_leg1_'_'_%stance'])
subplot(2,3,2);
hist(v1beg, histboxbeg);
subplot(2,3,3);
hist(v1end, histboxend);

histbox = (round(min(v2))-0.5):.001:(round(max(v2))-0.2);
histboxbeg = (round(min(v2beg))-0.5):.001:(round(max(v2beg))-0.2);
histboxend = (round(min(v2end))-0.5):.001:(round(max(v2end))-0.2);
subplot(2,3,4);
hist(v2, histbox);
subplot(2,3,5);
hist(v2beg, histboxbeg);
title([subnum'_leg2_'_'_%stance'])
subplot(2,3,6);
hist(v2end, histboxend);
%
%%
%Important DurattionVars
DurVar = zeros(18,1);
DurVar(1) = mean(stridetime);
DurVar(2) = mean(stridetimebeg);
DurVar(3) = mean(stridetimeend);
DurVar(4) = mean(stancetimes);
DurVar(5) = mean(stancetimesbeg);
DurVar(6) = mean(stancetimesend);
DurVar(7) = mean(v1);
DurVar(8) = mean(v1beg);
DurVar(9) = mean(v1end);
DurVar(10) = std(stridetime);
DurVar(11) = std(stridetimebeg);
DurVar(12) = std(stridetimeend);
DurVar(13) = std(stancetimes);
DurVar(14) = std(stancetimesbeg);
DurVar(15) = std(stancetimesend);
DurVar(16) = std(v1);
DurVar(17) = std(v1beg);
DurVar(18) = std(v1end);

DurVar2 = zeros(18,1);
DurVar2(1) = mean(stridetime2);
DurVar2(2) = mean(stridetimebeg2);
DurVar2(3) = mean(stridetimeend2);
DurVar2(4) = mean(stancetimes2);
DurVar2(5) = mean(stancetimesbeg2);
DurVar2(6) = mean(stancetimesend2);
DurVar2(7) = mean(v2);

```



```

DurVar2(8) = mean(v2beg);
DurVar2(9) = mean(v2end);
DurVar2(10) = std(stridettime2);
DurVar2(11) = std(stridettimebeg2);
DurVar2(12) = std(stridettimeend2);
DurVar2(13) = std(stancetimes2);
DurVar2(14) = std(stancetimesbeg2);
DurVar2(15) = std(stancetimesend2);
DurVar2(16) = std(v2);
DurVar2(17) = std(v2beg);
DurVar2(18) = std(v2end);

```

```

DurVarboth = zeros(6,1);
DurVarboth(1) = mean(si);
DurVarboth(2) = mean(sibeg);
DurVarboth(3) = mean(siend);
DurVarboth(4) = std(si);
DurVarboth(5) = std(sibeg);
DurVarboth(6) = std(siend);

```

```

eval(['DurVar' 'subnum' = DurVar; ']);
eval(['DurVar2' 'subnum' = DurVar2; ']);
eval(['DurVarboth' 'subnum' = DurVarboth; ']);

```



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